Catena 180 (2019) 224–237

Contents lists available at ScienceDirect

Catena

journal homepage: www.elsevier.com/locate/catena

Relative importance of climate change and human activities for vegetation changes on China's silk road economic belt over multiple timescales

Xiangzhen Qi, Junhe Jia, Huiyu Liu*, Zhenshan Lin

State Key Laboratory Cultivation Base of Geographical Environment Evolution (Jiangsu Province), Nanjing Normal University, Nanjing 210023, China
Key Laboratory of Virtual Geographic Environment (Nanjing Normal University), Ministry of Education, Nanjing 210023, China
Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing Normal University, Nanjing 210023, China
College of Geography Science, Nanjing Normal University, Nanjing 210023, China

ARTICLE INFO

Keywords:
Multiple timescale analysis
Climate change
Human activities
Spatial heterogeneity
Sustainable regional socioeconomic development

ABSTRACT

Ecological issues of China's Silk Road Economic Belt are receiving increasing attention. It is necessary to monitor vegetation changes in the Belt and explore their relationship with climate changes and human activities to ensure sustainable regional socioeconomic development. However, there is no adequate understanding of the relative importance of climate changes and human activities on vegetation over multiple timescales. In this study, ensemble empirical mode decomposition (EEMD) and residual trends (RESTREND) methods were used to establish the relative importance over multiple timescales. (1) The dominant timescales of vegetation changes have obvious spatial heterogeneity, which was affected by vegetation types and elevation. Grassland in high-altitude areas, needleleaf forest, and shrubland were characterized by 3-year oscillations. Low-altitude areas mainly covered by cropland were characterized by long-term trends. (2) Climate types mainly affected the relationship between vegetation and climate changes at short timescales, while vegetation types, elevation, landforms affected the relationship over each timescale. Over the 3-year timescale, temperature and precipitation had a negative and a positive relationship respectively with vegetation changes in semi-arid and arid regions, but a positive relationship and a negative relationship respectively in semi-humid and humid regions. As the timescale widened, temperature had a positive relationship in all areas, except for needleleaf forest, and precipitation had a positive relationship except in high-latitude areas dominated by alpine meadow and in karst areas. (3) Vegetation changes were dominated by human activities at 3- and 6-year timescales but by climate changes in the long-term trend. However, when considering the total effects of these three timescales, climate changes dominated the overall changes of vegetation, while human activities also played an important role in vegetation reduction and insignificant changes. Vegetation changes were influenced by cross-scale climate changes. This study showed that multiple timescale analysis could deepen our understanding of the roles of climate and human activities on vegetation changes.

1. Introduction

The “Belt and Road Initiative”, i.e., the Silk Road Economic Belt and the 21st Century Maritime Silk Road policy, proposed by China, for economic integration of China with Asia, Europe and Africa, has attracted more and more attention in both China and the rest of the world (Duan et al., 2018). China's Silk Road Economic Belt, a key part of the “Belt and Road Initiative”, is a new economic belt developed on land along the ancient Silk Road, which connects China and the West (Li et al., 2015). Its rebirth will inevitably bring enormous benefits to underdeveloped areas of west China. However, in Northwest China, the route passes through semi-arid and arid regions (Li et al., 2015), and in Southwest China, the route passes through humid areas but has the largest karst area (Hou et al., 2015). The Silk Road Economic Belt is, therefore, water resource-limited in the west and ecologically vulnerable in the east, which is highly sensitive to climate changes and human activities (Hou et al., 2015; Zhou et al., 2014; Li et al., 2016). It will be a huge challenge to ensure the New Silk Road to be built in a sustainable way that adequate attention is paid to the environment and any potential ecological damage is avoided (Li et al., 2015). Arid regions are predicted to become warmer and drier, and humid regions will become warmer and moister (Jiapaer et al., 2015; Li et al., 2016; Jiang et al.,

* Corresponding author at: State Key Laboratory Cultivation Base of Geographical Environment Evolution (Jiangsu Province), Nanjing Normal University, Nanjing 210023, China.
E-mail address: liuhuiyu@njnu.edu.cn (H. Liu).

https://doi.org/10.1016/j.catena.2019.04.027
Received 22 September 2018; Received in revised form 7 March 2019; Accepted 24 April 2019
0341-8162/ © 2019 Elsevier B.V. All rights reserved.

2017). Meanwhile, with economic development and an increase in population, human activities will pose great threats to vegetation (Li et al., 2016; Jiang et al., 2017). Climate changes and human activities on the new Silk Road will thus place a further strain on the limited water resources and vulnerable environments (Li et al., 2015). Vegetation plays an important role in the protection and restoration of fragile ecological environments (Piao et al., 2011; Hou et al., 2015; Jiang et al., 2015). Therefore, monitoring vegetation changes in the belt and exploring the relationships with climate changes and human activities will be important to ensure sustainable regional socioeconomic development.

Vegetation changes are commonly considered as indicators of environmental changes at various spatial and temporal scales (Wen et al., 2017) and are thought to be triggered by either climatic factors or human activities, or both (Zhou et al., 2014; Cai et al., 2015; Sun et al., 2015a; Huang et al., 2016; Wang et al., 2016; Y. Zhang et al., 2016). Quantifying the relative importance of climate changes and human activities on vegetation dynamics is critical for developing adaptation strategies to address the challenges posed by both of them for ecosystems (Jiang et al., 2017). Thus, there are an increasing number of studies to extract the human-induced and climate-driven vegetation changes (Li et al., 2016; Huang et al., 2016; Jiang et al., 2017). The relative importance of climate changes and human activities for vegetation changes were thought to differ according to location, vegetation types and targeted periods (Zhou et al., 2014; Cai et al., 2015; Sun et al., 2015a; Wang et al., 2016; Huang et al., 2016; Li et al., 2016). However, their relative importance at different timescales such as annual, interannual, decadal and more longer time scales is unclear. In fact, vegetation time series and their driving forces are nonlinear and nonstationary, which involve a combination of seasonal, annual, interannual, decadal and abrupt changes (Hawinkel et al., 2015; Liu et al., 2017; Wen et al., 2017). Thus, the relationships between vegetation and climate changes and human activities and their relative importance are dependent on timescales (Hawinkel et al., 2015; Liu and Menzel, 2016; Liu et al., 2017). Although previous studies revealed the relationship between vegetation dynamics and climate change at multiple timescales such as monthly, seasonally and annually, they made a linear and stationary assumption (Jiapaer et al., 2015; R. Zhang et al., 2016; Pang et al., 2017; Kong et al., 2017). It is, therefore, necessary to choose an appropriate method to understand the relationship of climate changes and human activities with vegetation dynamics, and their relative importance at different timescales under a nonlinear and nonstationary assumption (Yin et al., 2016). The Ensemble Empirical Mode Decomposition (EEMD, Wu and Huang, 2005, 2009), a signal processing tool generated on the basis of Empirical Mode Decomposition (EMD, Huang et al., 1998), has a significant advantage in dealing with nonstationary signals. It naturally decomposes the data into a number of intrinsic mode function (IMF) components representing oscillations of different timescales and a residue representing long-term trend. They are now applicable to vegetation time series for multiple timescale analysis (Hawinkel et al., 2015; Yin et al., 2016; Liu et al., 2017; Wen et al., 2017). Although Liu et al. (2018) have explored the relationship between vegetation dynamics and climate at multiple time scales in Southwest China based on EEMD, they have only quantified the relative importance of climate changes and human activities as a whole, but not over different timescales.

Normalized difference vegetation index (NDVI), chlorophyll sensitive, can be used to quantify the vegetation changes by measuring the contrast between the red and near-infrared reflections of solar radiation (Paruelo et al., 1997). With the development of remote sensing, NDVI is extensively applied to monitor vegetation changes (Piao et al., 2011; Jiang et al., 2015; Wen et al., 2017; Jiang et al., 2017). Hence, in this study NDVI was used to monitor vegetation changes. Vegetation and climate changes at multiple timescales were extracted using the EEMD method and their relationships at multiple timescales were further revealed. Due to the lack of long-term data of human activities, the residual trends method (RESTREND, Evans and Geerken, 2004) was widely used to reveal the relative roles of climate changes and human activities to provide scientific references for vegetation conservation and restoration in fragile ecosystems (Cai et al., 2015; Sun et al., 2015a, 2015b). The objectives of this study are to determine the following:

(1) The dominant timescales of vegetation dynamics and their spatial heterogeneity.
(2) Spatial heterogeneity of the relationships between vegetation and climate changes at different timescales.
(3) The relative importance of climate changes and human activities for vegetation changes over different timescales.

2. Data and methods

2.1. Study area

China's Silk Road Economic Belt (73°26′E–112°04′E, 20°53′N–49°12′N), including five provinces in Northwest China as Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang; four provinces in Southwest China as Chongqing, Sichuan, Yunnan and Guangxi. China's Silk Road Economic belt is vast and rich in mineral resources, energy resources, land resources and valuable tourism resources, known as the 21st century strategic energy and resource base.

In this study area, elevation ranges from −155 m to 8058 m (Fig. 1a). The climate of China's Silk Road Economic Belt is diverse, the northwest area is a temperate continental climate with annual precipitation below 800 mm and temperature below 20 °C, including semi-arid, arid, and semi-humid areas. However, the southern area is a subtropical monsoon climate with annual precipitation above 800 mm and temperature above 20 °C, mainly humid area. High-altitude areas such as Tianshan mountain, BayanKela mountain and Kunlun Mountain are plateau climate with temperature below −10 °C (Fig. 1b–c). This study region is mainly covered by grassland, cropland, needleleaf forest, and sparse vegetation (Fig. 1d).

2.2. Data sources and methods

2.2.1. Normalized difference vegetation index (NDVI) dataset

The NDVI dataset at a spatial resolution of 8 km and 15-day interval from 1982 to 2015 was downloaded from the AVHRR NDVI dataset published by the Global Inventor Modeling and Mapping Studies (GIMMS) project (Pinzon and Tucker, 2014). The AVHRR NDVI3g.V1 dataset has been widely used to monitor vegetation dynamic due to its capability of providing the longest time-series record from the early 80s (Huang and Kong, 2016). In order to improve the quality of remote sensing data, especially to eliminate the cloud-contaminated data and abnormal data, the Savitzky-Golay filter was applied to smooth the NDVI data. The maximum-value composite (MVC) method was used to choose the higher value of semi-monthly NDVI to compile the monthly NDVI (Holben, 1986). To reflect the vegetation more appropriately, the NDVI products were averaged over the entire growing season from May to October (Northwest China) and from April to November (Southwest China) to get growing-season NDVI. Regions of growing-season NDVI values below 0.1 in the growing season are recognized as nonvegetated areas or bare soil (Jamali et al., 2014). Therefore, only the pixels with NDVI > 0.1 were used to represent the vegetated areas.

2.2.2. Meteorological and DEM data

The meteorological data, including monthly average temperature and precipitation data, were collected by approximately 279 weather stations provided by China Meteorological Science Data Sharing Service Network (http://www.nmic.cn/) during1982–2015. We used thin-plate-smoothing spline-fitting techniques in ANUSPLIN 4.4 (Hutchinson and Xu., 2013, http://fennerschool.anu.edu.au/research/products/anusplin-vrsn-44) to interpolate the meteorological data into same

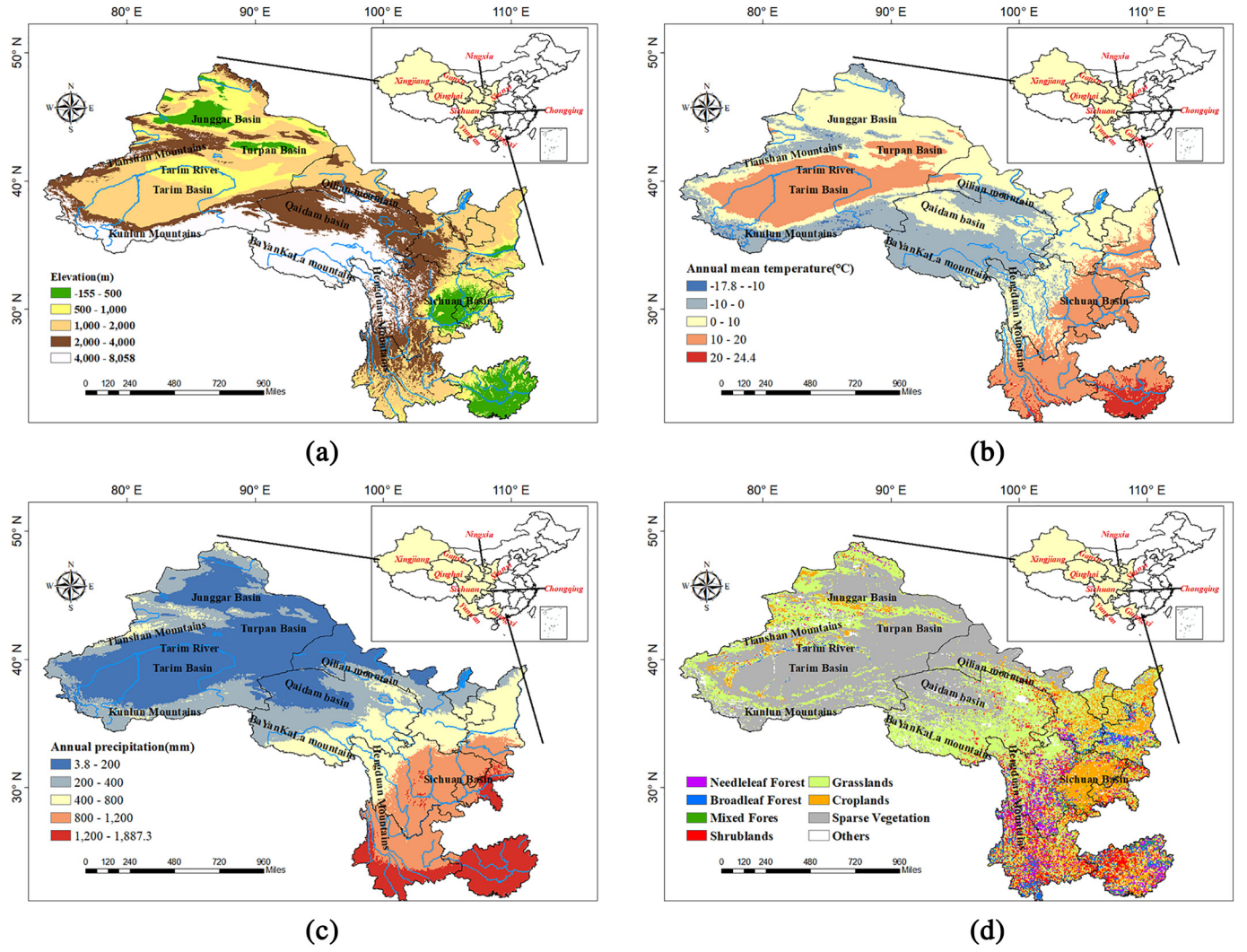


Fig. 1. Study area. (a) elevation; (b) annual mean temperature; (c) annual precipitation; (d) vegetation types.

spatial resolution as NDVI data with elevation, latitude, and longitude as covariates. Elevation data was downloaded from the Cold and Arid Regions Science Data Centre at Lanzhou (WestDC, http://westdc.westgis.ac.cn).

2.2.3. Vegetation type

The vegetation type data in 2000 was derived from IGBP land cover classification system with a resolution of 1 km and was divided into 17 vegetation types (http://westdc.westgis.ac.cn/data/, Ran et al., 2009). The data was resampled to a resolution of 8 km with the nearest-neighbor approach and the original vegetation types were merged into eight categories (needleleaf forest, broadleaf forest, mixed forest, shrubland, grassland, cropland, sparse vegetation and others, Fig. 1d).

2.3. Methods

2.3.1. Ensemble empirical mode decomposition (EEMD)

In this paper, EEMD was used to analyze the characteristics of vegetation and climate changes at pixel scale at multiple timescales.

The EEMD method decomposes the original data sequence $x(t)$ into n components, called the intrinsic mode function (IMF_i, $i = 1, 2..., n$) and a residual. Each IMF component and the residual represent the oscillation at one timescale and the long-term trend of the original sequence, respectively. The basic idea of the EEMD method is as follows:

To get a number of noisy pseudo signals $X_j(t)$, a number (np) of realizations of Gaussian white noise $\omega_j(t)$ was added to the original $x(t)$.

$$X_j(t) = x(t) + \omega_j(t), j = 1, 2, ...np \tag{1}$$

np was usually adopted as 1000.

Then, EMD method (Huang et al., 1998) was used to decompose $X_j(t)$ to get the IMF components (c_{ij}) and the residue (r_{nj}) as the following (the detailed process of EMD can be seen in Liu et al., 2017, 2018):

$$X_j(t) = \sum_{i=1}^{n} c_{ij} + r_{nj} \tag{2}$$

where c_{ij} and r_{nj} denote the ith IMF and residue from $X_j(t)$ with EMD method.

Finally, average the corresponding EMD IMF components and residues of these noisy pseudo signals to get the ith EEMD IMFs $c_i(t)$ and r_n as the following:

$$c_i(t) = \frac{1}{np} \sum_{j=1}^{np} c_{ij}(t) \tag{3}$$

and

$$r_n = \frac{1}{np} \sum_{j=1}^{np} r_{nj}(t) \tag{4}$$

The mean period of the ith IMF component was calculated by

dividing the time length (N) with the number of its peaks (local maxima). To assess the relative importance of each IMF component and the residue, variance contributions (V_i and V_r for the ith IMF component and residue r_n, respectively) were figured out as the following:

$$V_i = Vr(c_i) / \left[\sum_{i=1}^{n} Vr(c_i) + Vr(r_n) \right] \tag{5}$$

and

$$V_r = Vr(r_n) / \left[\sum_{i=1}^{n} Vr(c_i) + Vr(r_n) \right] \tag{6}$$

where $Vr(c_i)$ and $Vr(r_n)$ are the variance of the ith IMF component and residue (r_n).

2.3.2. Mann–Kendall trend test method

The Mann–Kendall trend test (Mann, 1945; Kendall, 1975) is a nonparametric statistical test, which does not require the independence and normality of the time series data and can well detect the long-term trend.

In the Mann–Kendall trend test, the test statistics Z can be calculated as follows:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{\mathrm{var}(S)}} & S > 0 \\ 0 & S = 0 \\ \dfrac{S+1}{\sqrt{\mathrm{var}(S)}} & S < 0 \end{cases} \tag{7}$$

where:

$$S = \sum_{i=1}^{n-1} \sum_{k=i+1}^{n} sign(x_k - x_i) \tag{8}$$

$$\mathrm{var}(S) = \frac{n(n\text{-}1)(2n+5)}{18} \tag{9}$$

$$\mathrm{sign}(x_k - x_i) = \begin{cases} 1 & x_k - x_i > 0 \\ 0 & x_k - x_i = 0 \\ -1 & x_k - x_i < 0 \end{cases} \tag{10}$$

where n is the length of time series, x_k and x_i are the data values at times k and i ($k > i$), and $\mathrm{sign}(x_k - x_i)$ is the symbolic function.

$Z > 0$ and $Z < 0$ indicate an increasing or decreasing trend, respectively. At a given significance level α, when $|Z| > u_{1-\alpha/2}$, it represents a significant change in the time series at α level. In this study, $\alpha = 0.05$ was used, and then $u_{1-\alpha/2} = 1.96$. Thus, $Z > 1.96$ or $Z < -1.96$ indicated a significant increase or decrease in vegetation, and $-1.96 < Z < 1.96$ indicated insignificant changes in vegetation.

2.3.3. Residual trend (RESTREND) method

Because long time series of human activities such as grazing, mining and environmental management is hard to obtain, we assumed that NDVI was only affected by climate changes and human activities, and thus used the RESTREND method to extract the relative roles of climate changes and human activities. The RESTREND method can investigate trends in residual differences between observed NDVI ($NDVI_{obs}$) and predicted NDVI ($NDVI_{pre}$) by using a regression model involving climate factors as the explanatory variables (Evans and Geerken, 2004; Cai et al., 2015; Sun et al., 2015a). The basic idea of the RESTREND method is as follows:

Establish a regression model between $NDVI_{pre}$ and climate factors (precipitation, P and temperature, T) as follows:

$$NDVI_{pre_{i,j}} = b_0 + b_1 P_{i,j} + b_2 T_{i,j} \tag{11}$$

wherein: $P_{i,j}$, $T_{i,j}$ indicate the cumulative precipitation and the mean temperature during the growing season respectively in the spatial position of the i-th row and the j-th column; b_0, b_1, b_2 are the undetermined coefficients determined by the least squares method.

Then, we calculate the residual difference between $NDVI_{obs}$ and $NDVI_{pre}$, and define the residual difference as $NDVI_{res}$. In this study, the impact of climate changes was measured by the trends of $NDVI_{pre}$, and the impact of human activities was represented by the trends of $NDVI_{res}$. To extract the relative effects of climate changes and human activities on vegetation changes, we calculated the trends of $NDVI_{pre}$ values, $NDVI_{obs}$ and $NDVI_{res}$ using the Sen-slope method (Sen, 1968).

Sen-slope method uses the median value of the slope sequence as the basis of the trend judgment, which can eliminate the influence of data deletion or abnormality on the trend test to a certain extent (Sen, 1968). The Sen-slope formula is:

$$Sen = Median\left[\frac{(NDVI_n - NDVI_m)}{n-m} \right], \forall\ n > m \tag{12}$$

where Sen is the Sen-slope value; $NDVI_m$ and $NDVI_n$ are the sequence values of m and n respectively, $1 \le m < n \le k$, k is the sequence length. Then we can calculate the $Sen_{NDVI_{obs}}$, $Sen_{NDVI_{pre}}$ and $Sen_{NDVI_{res}}$ according to Eq. (12).

Finally, we calculated the relative roles of climate variations and human activities in vegetation change based on $Sen_{NDVI_{obs}}$, $Sen_{NDVI_{pre}}$ and $Sen_{NDVI_{res}}$ as shown in Table 1 (Sun et al., 2015a; Guo et al., 2017; Ma et al., 2017).

3. Results

3.1. Mann–Kendall trend and multi-timescale analyses for growing-season NDVI

The Mann–Kendall trend analysis for NDVI was performed to reveal the trend of vegetation changes between 1982 and 2015 (Fig. 2). Significant vegetation increases were mainly observed in the east and northwest areas at low altitudes, whereas insignificant changes were observed in most of the southwest areas.

To explore vegetation changes over different timescales in the One Belt (China's Silk Road Economic Belt), the EEMD method was used for multiple timescale analysis of the growing-season NDVI between 1982 and 2015 at the pixel scale. The periods of each IMFs and the variance contributions of each IMF and residue were averaged for all pixels, and thus get the averaged periods and variance contributions, and their standard deviations (Table 2). The four IMFs and residues of all pixels were averaged to get the averaged vegetation changes during the growing season at different timescales for all pixels (Fig. 3).

As shown in Table 2 and Fig. 3, growing-season NDVI can be decomposed into four IMF components and a residual component in this study area, representing 3-, 6-, 15-, 32-year timescales and a long-term trend. The residual curve showed an upward trend with 31.69% variance contribution, indicating a substantial increase in vegetation during the past 34 years, which is consistent with the Mann–Kendall trend. Of the four IMFs, IMFs 1 and 2 had relatively large contributions, indicating that growing-season vegetation was dominated by the interannual variations of 3- and 6-year timescales. Moreover, the standard deviations of IMFs 1–2 and the residual are large, which means oscillations of these three timescales have high spatial heterogeneity. Because the contributions of IMFs 3 and 4 were < 10%, this study will focus on the 3- and 6-year timescales and the long-term trend.

Fig. 4 shows the spatial heterogeneity of the variance contributions of NDVI over 3- and 6-year timescales and the long-term trend. In the east of the Belt, at an elevation below 2000 m, the variance contribution of 3-year timescale for cropland was < 30%, whereas the contribution of the long-term trend was > 40%, indicating that long-term trends were most important in this area. In contrast, in the west of the Belt, at an elevation higher than 2000 m covered by grassland and the areas dominated by needleleaf forests and shrublands, the variance

Table 1
Methods for assessing the relative roles of climate changes and human activities in vegetation changes under different scenarios.

$Sen_{NDVI_{obs}}$	$Sen_{NDVI_{pre}}$	$Sen_{NDVI_{res}}$	Relative contribution of climate changes (%)	Relative contribution of human activities (%)	Explanation
< 0	> 0	< 0	0	100	Human-dominated vegetation decrease
	< 0	> 0	100	0	Climate-dominated vegetation decrease
	< 0	< 0	$\frac{\lvert Sen_{NDVI_{pre}}\rvert}{\lvert Sen_{NDVI_{pre}}\rvert + \lvert Sen_{NDVI_{res}}\rvert} \times 100$	$\frac{\lvert Sen_{NDVI_{res}}\rvert}{\lvert Sen_{NDVI_{pre}}\rvert + \lvert Sen_{NDVI_{res}}\rvert} \times 100$	Both climate and human induced vegetation decrease, relative contributions > 50% represent dominant
	> 0	> 0	–	–	Error (because both climate and human activities contributed to vegetation increase, but vegetation decreased)
> 0	< 0	> 0	0	100	Human-dominated vegetation increase
	> 0	< 0	100	0	Climate-dominated vegetation increase
	> 0	> 0	$\frac{\lvert Sen_{NDVI_{pre}}\rvert}{\lvert Sen_{NDVI_{pre}}\rvert + \lvert Sen_{NDVI_{res}}\rvert} \times 100$	$\frac{\lvert Sen_{NDVI_{res}}\rvert}{\lvert Sen_{NDVI_{pre}}\rvert + \lvert Sen_{NDVI_{res}}\rvert} \times 100$	Both climate and human induced vegetation increase, relative contributions > 50% represent dominant
	< 0	< 0	–	–	Error (because both climate and human activities contributed to vegetation decrease, but vegetation increased)

contribution of 3-year timescale was > 50%, the contribution of 6-year timescale was between 20%–30% and the contribution of the long-term trend was < 30%. It indicated that these areas were dominated by vegetation oscillations of 3-year timescale; meanwhile, the 6-year timescale oscillations were also important.

3.2. Relationships between vegetation and climate changes at different timescales

To explain the relationships between vegetation and climate changes at different timescales, the EEMD method was used for multiple timescale analyses of growing-season average temperature and precipitation between 1982 and 2015 at pixel scale. In a similar way as Fig. 3, Fig. 5 shows the averaged changes of growing-season average temperature and precipitation at different timescales. Table 3 shows the average periods and their variance contributions at different timescales in all pixels, similarly with Table 2.

The growing-season average temperature in the study area had four IMF components over 3-, 6-, 19- and 34-year timescales, respectively, along with a residue (Fig. 5a and Table 3). The variance contributions of IMFs at 3- and 6-year timescales were greater than the other IMFs. However, the residual contribution was 41.37% and greater than all IMFs, indicating that the growing-season temperature showed a substantial increasing trend.

The growing-season precipitation in the study areas was separated into 3-, 6-, 14- and 22-year oscillations (Fig. 5b and Table 3) and a residue. The contributions of the 3- and 6-year oscillations were much greater than the others. The variance contribution of the long-term trend was very low (below 10%). Therefore, the growing-season precipitation was characterized by 3- and 6-year oscillations with no substantial long-term trend.

To reveal the spatial heterogeneity of the relationships between vegetation and climate changes in the growing season, per-pixel partial correlation analysis was performed for NDVI and meteorological factors (temperature and precipitation) at 3- and 6-year timescales and over the long-term trend (Fig. 6). The area percentages for different relationships between growing-season NDVI and climate changes at these two timescales and over the long-term trend are shown in Table 4.

As shown from Fig. 6a and Table 4, most of the areas showed an insignificant relationship between NDVI and temperature at the 3-year timescale. Only 5.17% and 7.99% of areas, respectively, showed significantly negative or positive relationships between vegetation changes and temperature. In most semi-arid (200 mm < precipitation amount < 400 mm) and arid (precipitation amount < 200 mm) regions, temperature was negatively related to vegetation. However, in most semi-humid (400 mm < precipitation amount < 800 mm) and humid (precipitation amount > 800 mm) regions, temperature was positively associated with vegetation changes, apart from needleleaf forest, where it had a negative relationship. In most study areas, precipitation was insignificantly related to vegetation changes; only 6.01% of areas showed a significantly negative relationship and only 5.96% of areas showed a significantly positive relationship (Fig. 6b and Table 4). In semi-arid and arid regions, precipitation had a positive relationship with vegetation changes. In contrast, precipitation had a negative relationship with vegetation changes in humid and semi-humid regions. Meanwhile, in arid and semi-arid regions, the area with vegetation changes that were significantly correlated with precipitation was much larger than the area where vegetation was significantly correlated with temperature. However, the area with vegetation changes significantly correlated with temperature was larger than the area with vegetation that was significantly correlated with precipitation in semi-humid and humid regions.

At the 6-year timescale, the area with significant relationships between vegetation changes and temperature increased to 22.07% of the total area studied and was common in humid and semi-humid regions (Fig. 6c and Table 4). The area showing significantly positive

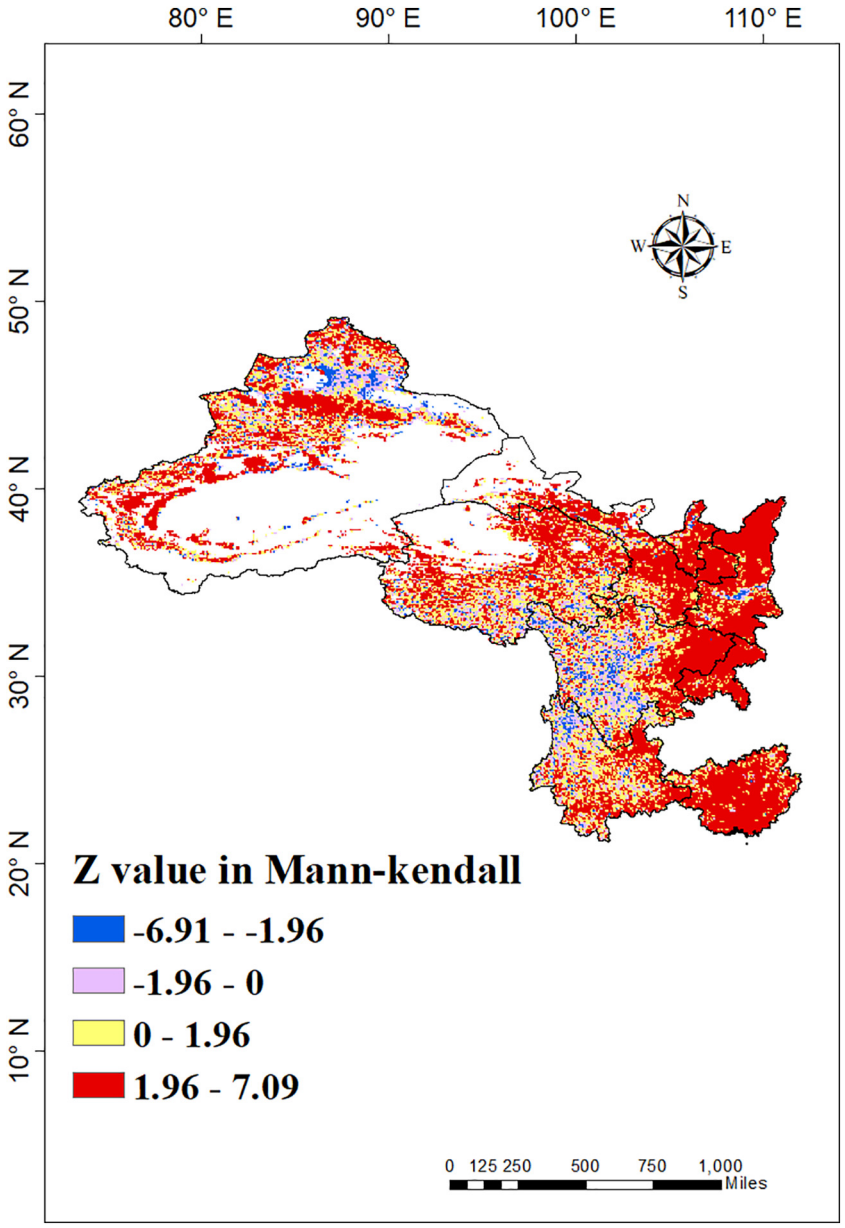


Fig. 2. Trend of growing-season NDVI between 1982 and 2015 based on Mann–Kendall test. Z values < -1.96 or > 1.96 indicate a significant decrease or increase at the 95% confidence level.

relationships between vegetation changes and precipitation increased from 5.96% to 20.84% and was common in arid and semi-arid regions (Fig. 6d and Table 4). In humid and semi-humid regions, the relationships between vegetation changes and precipitation were still negative, with a subtle increase in the area with a significant relationship. However, in Yunnan and Guangxi provinces with a subtropical monsoon climate, the relationship changed from negative to positive. The increase in the area with a significant relationship between vegetation changes and precipitation was a little greater than the increase in the area with a significant relationship between vegetation changes and temperature.

In the majority of the study area, long-term temperature increase promoted vegetation increase (Fig. 6e). However, in high mountain areas with an elevation above 4000 m and areas dominated by needleleaf forest, long-term temperature rise will prevent vegetation increase. In most of the study area, long-term precipitation increase promoted vegetation increase (Fig. 6f). However, in karst areas and regions with an elevation above 4000 m dominated by alpine meadows, long-term precipitation increase prevented vegetation increase. Thus, on long-term trend, the relationship between vegetation and climate changes was affected by vegetation types, elevation, and landform. The area showing significantly positive relationships between vegetation

Table 2
Averaged periods of vegetation changes in growing season at different time scales (values in brackets are the standard deviations) and their variance contributions.

	IMF1	IMF2	IMF3	IMF4	Residue
Period (timescale/a)	3 (0.32)	6 (1.13)	15 (5.06)	32 (10.94)	–
Variance contribution (%)	39.43 (17.80)	17.26 (11.41)	9.15 (8.00)	2.48 (4.03)	31.69 (24.28)

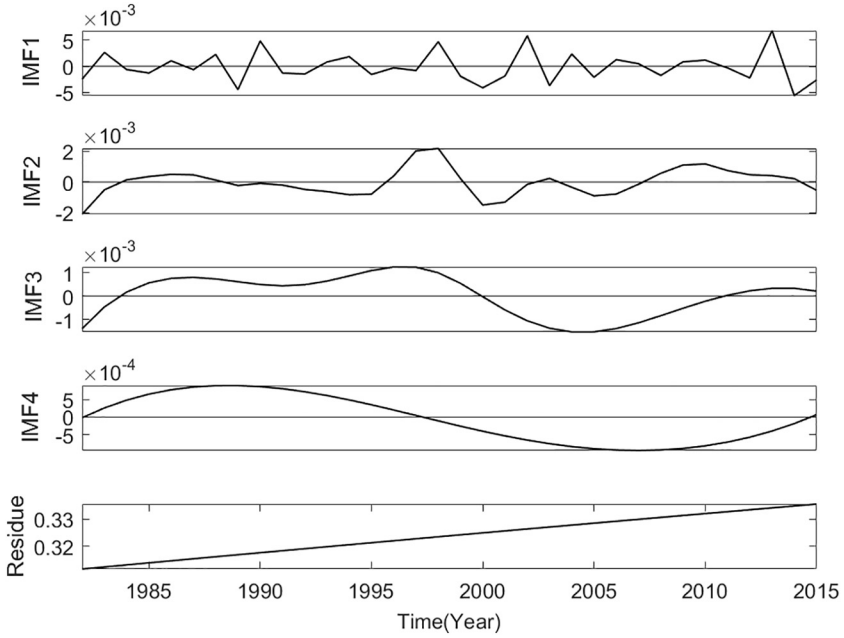


Fig. 3. Averaged changes of growing-season NDVI at different timescales at the pixel scale.

changes and temperature and precipitation also showed significant vegetation increase (Fig. 2).

The relationships between vegetation changes and temperature and precipitation became increasingly significant as the timescale widened (Table 4). The area showing significant relationships between NDVI and temperature increased from 13.16% at the 3-year timescale to 22.07% at the 6-year timescale and 99.72% over the long-term trend. In contrast, the area showing significant relationships between NDVI and precipitation increased from 11.97% to 28.49% and finally to 99.76%. In particular, the area with a significantly positive relationship was much larger than the area with a significantly negative relationship. Therefore, climate change had stronger and more positive influences on vegetation changes as timescales increased.

3.3. Relative importance of climate changes and human activities for vegetation changes over different timescales

We used IMF1 of NDVI as a dependent variable and IMF1s of temperature and precipitation as covariates in the RESTREND method to establish the relative importance of climate changes and human activities for vegetation changes over the 3-year timescale. In similar manner, we also established their relative importance over 6-year timescale and the long-term trend. We also used the original value of NDVI as a dependent variable and the six components of IMF1s and IMF2s and the residual values of temperature and precipitation as covariates to establish their relative importance for the overall changes of vegetation. Fig. 7 and Table 5 show the relative importance of climate changes and the percentage area of climate-dominated and human-dominated vegetation changes over different timescales and as a whole when considering these three timescales.

As shown in Fig. 7 and Table 5, over the 3-year timescale vegetation changes in 78.87% of the study area (65.26% for vegetation increase and 16.62% for vegetation decrease) were driven by human activities (relative contribution of climate change < 50%), and in these areas, the relative contribution of climate changes is smaller than 25%. Climate-dominated vegetation changes (relative contribution > 50%) occurred in the boundary of the study area where vegetation changes were significantly related to temperature and precipitation. Over the 6-year timescale, human-dominated vegetation changes occurred in 77.69% of the area. The areas with climate-dominated vegetation increase expanded to 18.06% and were predominant in the east at low altitudes. Over the long-term trend, vegetation changes in 99.83% of the study area were mainly driven by climate changes. Moreover, in almost the entire study area, the contribution of climate changes to vegetation changes was > 75%. Therefore, vegetation changes were mainly driven by human activities over the 3- and 6-year timescales, but by climate changes over the long-term trend. Human effects on vegetation decreased as the timescales widened, but the opposite occurred for climatic impacts.

When considering overall changes of 3- and 6-year timescales and residue, in 83.97% of the study area, vegetation changes were dominated by climate changes, especially in the areas where vegetation increased significantly. In areas where vegetation decreased (21.09%), the proportion that was climate-dominated area (14.83%) was larger than the proportion that was human-dominated area (6.26%). However, human activities also played an important role. Only 16.02% of vegetation changes were dominated by human activities, mostly occurred in insignificantly changed areas. About 41.81% of the study area showed insignificant changes, of which 12.26% was human-dominated. Human activities thus played an important role in areas with insignificant vegetation changes as a whole.

4. Discussion

4.1. Mann–Kendall trend and multiple timescale analysis of vegetation changes

Previous studies found significant NDVI increase in semi-arid and arid regions (Du et al., 2015; Li et al., 2015; R. Zhang et al., 2016), southwest China (Tong et al., 2017), and insignificant changes in southeast Qinghai–Tibet Plateau (Wang et al., 2016; Li et al., 2016). Through Mann–Kendall trend analysis, our studies also showed that in semi-arid and arid regions, vegetation showed a significant increasing trend consistent with previous studies (Du et al., 2015; Li et al., 2015; R. Zhang et al., 2016). However, in humid and semi-humid areas, the trends of vegetation changes were affected by elevation. In high-altitude areas, vegetation changes had an insignificant trend, while in low-altitude areas, vegetation showed a significant increasing trend.

Using the EEMD method, vegetation changes can be separated into four IMF components and a residue: the oscillations at 3-, 6-, 15- and

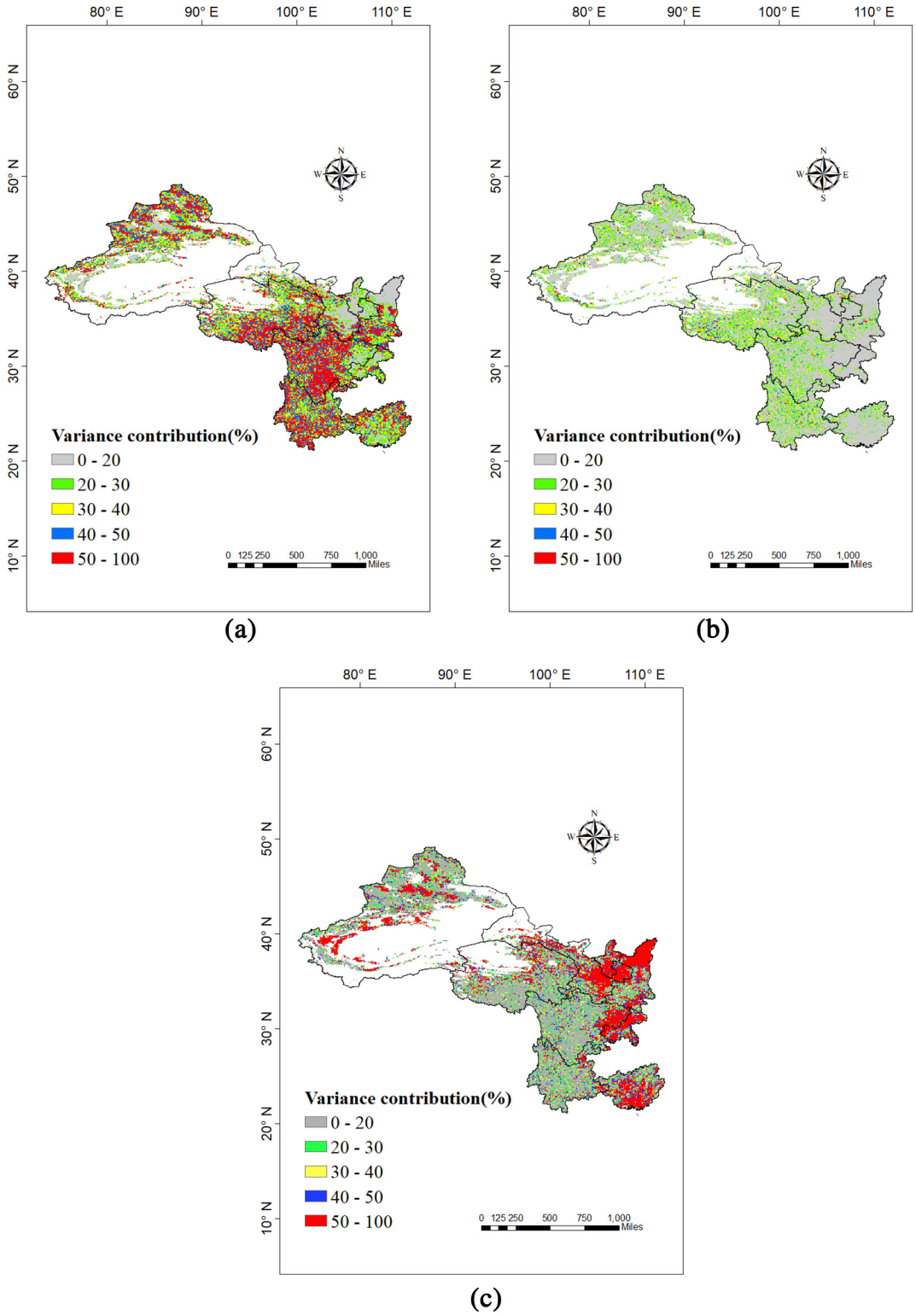


Fig. 4. Spatial distribution of variance contributions of 3-year timescale (a), 6-year timescale (b) and long-term trends (c) to vegetation changes.

32-year timescales and the increasing trend. Vegetation was characterized by oscillation of the 3-year timescale and the long-term trend. Vegetation changes over different timescales had obvious spatial heterogeneity, which was affected by elevation and vegetation types. In the east of the study area at an elevation below 2000 m, an area dominated by croplands, vegetation changes were characterized by a long-term trend. Moreover, those areas showed significant vegetation increases. In contrast, in the west, at an elevation above 2000 m covered by grassland, and the area dominated by needleleaf forest and shrubland, vegetation was dominated by 3-year timescale oscillation. It could be due to the fact that in high-altitude areas, the ecological environment is fragile, climatic conditions are harsh and vegetation growth is susceptible to human activities.

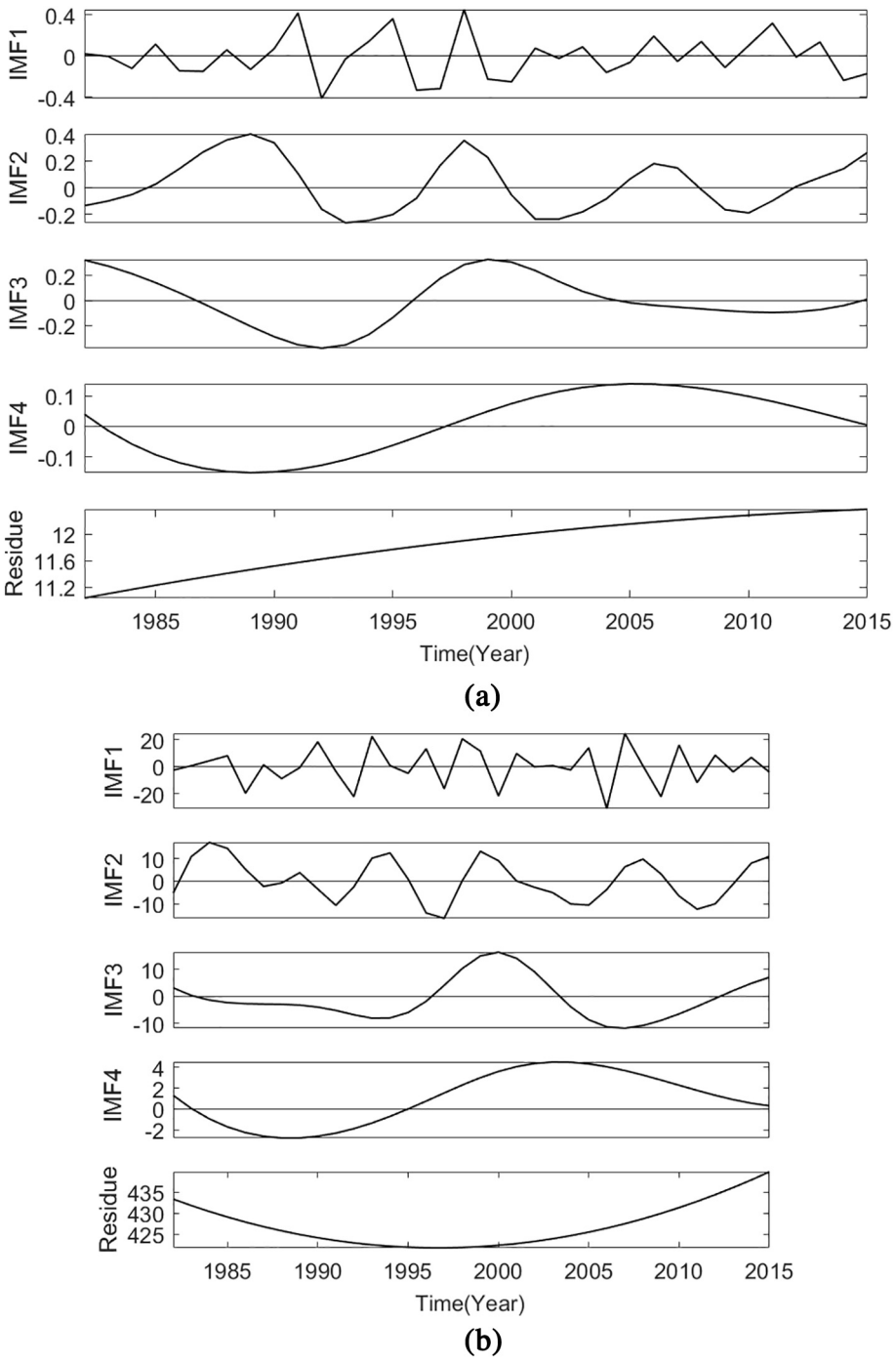
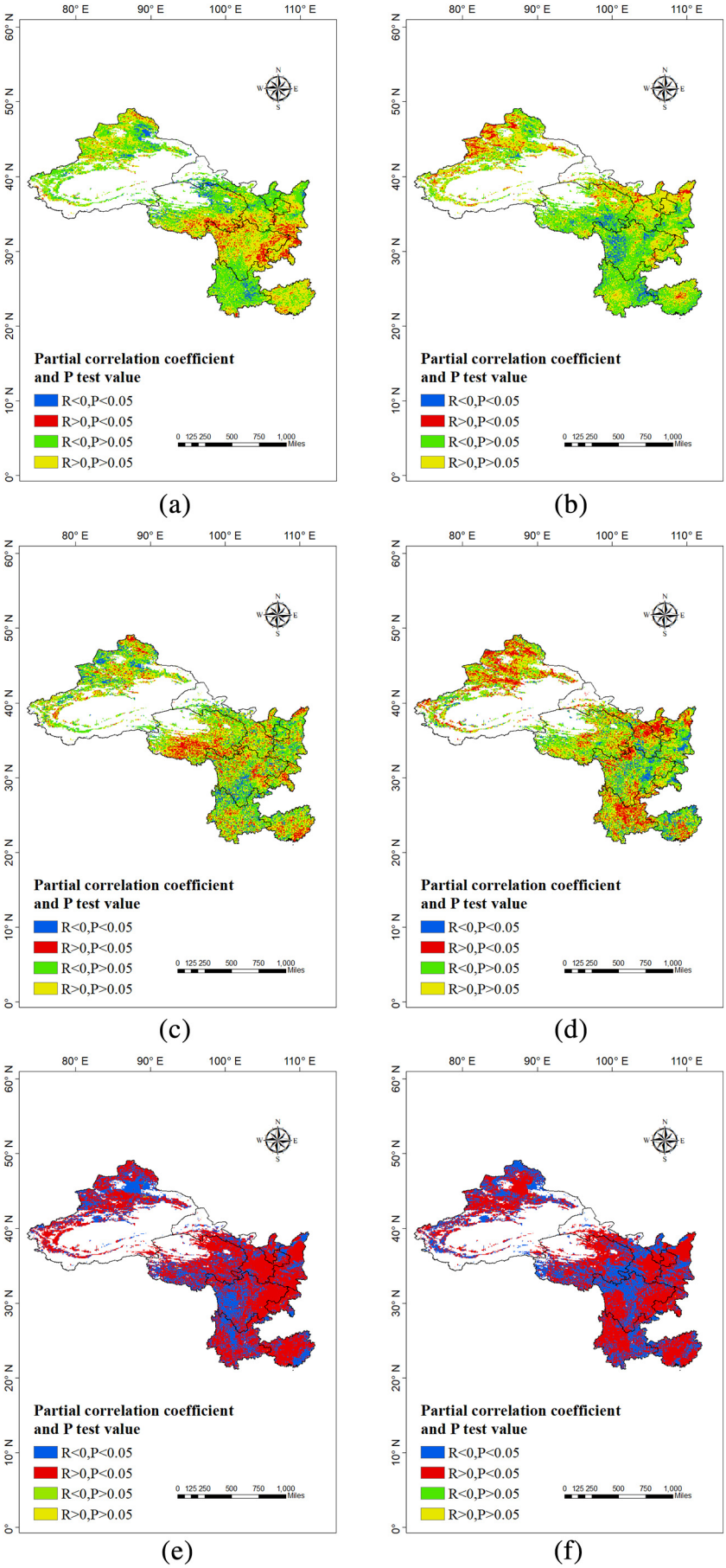


Fig. 5. Averaged changes of growing-season average temperature (a) and precipitation (b) at different timescales at the pixel scale.

Table 3
Averaged periods of growing-season average temperature and precipitation changes at different timescales in all pixels (values in brackets are the standard deviations) and their variance contributions.

		IMF1	IMF2	IMF3	IMF4	Residue
Temperature	Periods (timescale/a)	3 (0.35)	6 (1.35)	19 (3.72)	34 (7.19)	–
	Variance contribution (%)	27.89 (13.10)	16.29 (8.75)	10.46 (7.45)	4.00 (5.97)	41.37 (19.24)
Precipitation	Periods (timescale/a)	3 (0.26)	6 (1.08)	14 (4.48)	22 (9.29)	–
	Variance contribution (%)	57.31 (11.92)	20.42 (10.74)	8.76 (6.55)	4.34 (6.16)	9.17 (7.74)



(caption on next page)

Fig. 6. Relationships of NDVI with climate change during the growing season. (a), (c), (e) Represent the relationships with temperature, and (b), (d), (f) represent the relationships with precipitation at 3- and 6-year timescales and over the long-term trend, respectively.

4.2. Relationship between vegetation and climate changes at multiple timescales

In our study, we found that the relationships between vegetation and climate change were not only affected by climatic types (Molnar et al., 2010; Huang et al., 2016), vegetation types (Jiapaer et al., 2015) and elevation (Hou et al., 2015), but also varied according to timescales.

At short timescales as 3- and 6-year, vegetation changes had a negative relationship with temperature in arid and semi-arid regions, but with less significance, which was consistent with previous study (Xu et al., 2016). In regions without abundant precipitation, short-term temperature rise increases evaporation, which prevents vegetation growth (Huang et al., 2016; Huang and Kong, 2016). However, as the timescale widens, the relationship changed from negative to positive and gained greater significance. Long-term temperature increase promotes photosynthesis, further favoring vegetation growth (Huang and Kong, 2016; Hua et al., 2017). In humid and semi-humid regions with abundant precipitation, increased temperature will not affect water availability but will promote photosynthesis. Therefore, temperature had a positive relationship with vegetation changes over each timescale (Xie et al., 2016). However, vegetation types and landforms affect the relationship. In needleleaf forests and karst areas, temperature had a negative relationship with vegetation changes. Needleleaf forest is more suited to low-temperature areas. As the karst areas have low water-soil conservation ability (Jiang et al., 2014), rise in temperature will increase evaporation and further prevent vegetation growth. Thus, climate types mainly affected the relationships between temperature and vegetation changes over short timescales, while vegetation types mainly affected the relationship over long-term trend.

Precipitation had a positive relationship with vegetation growth in semi-arid and arid regions; however, this relationship was less significant in humid regions (Bai et al., 2004; Xie et al., 2016; Rishmawi et al., 2016). Our studies also showed that precipitation was positively related to vegetation changes at each timescale in semi-arid and arid regions. In semi-humid and humid regions, precipitation had a negative but insignificant relationship with vegetation changes at the 3- and 6-year timescales. However, long-term precipitation increase favored vegetation growth except that in karst areas and areas at an elevation above 4000 m dominated by alpine meadows, precipitation increase will not encourage vegetation growth. Since the grass roots are short and the landforms are complex in the alpine meadows, excessive precipitation will cause water and soil erosion, which is not favorable for vegetation growth (Wang et al., 2008; Jiapaer et al., 2015). In karst areas, increased precipitation can easily cause soil and water erosion and thus prevent vegetation growth. Thus, landform, elevation and vegetation types changed the relationship between precipitation and vegetation, while climate types mainly affected the relationship at short timescales.

Some studies showed that vegetation in Northwest China (arid and semi-arid areas) is strongly correlated with both temperature and precipitation (Zhou et al., 2014; Jiapaer et al., 2015). However, over short timescales, the areas showing insignificant relationship were much larger than those showing significant relationship. In the southwest (semi-humid and humid areas), the correlation between vegetation and temperature is stronger than the correlation between vegetation and precipitation (Hou et al., 2015). In our study, the areas showing a significant relationship between temperature and vegetation changes were larger than those showing a significant relationship between precipitation and vegetation changes. These findings indicated that precipitation was more important than temperature in arid and semi-arid areas, whereas temperature was more important in humid and semi-humid areas at short timescales, which is consistent with the previous studies (Xu et al., 2011; R. Zhang et al., 2016; Hua et al., 2017). However, over the long-term trend, temperature and precipitation were both significantly and positively correlated with vegetation changes, except in needle forest, karst and high-elevation areas.

4.3. Relative importance of climate changes and human activities for vegetation changes

Climate and human activities played different roles in vegetation dynamics according to spatial location, targeted period and vegetation type (Zhou et al., 2014; Sun et al., 2015a; Wang et al., 2016; Li et al., 2016). However, our results showed that the roles played by climate changes and human activities also differed according to timescales. At short 3- and 6-year timescales, in most of the study area, the relative contribution of climate changes was smaller than 25%. Vegetation changes are not only influenced by climate changes and human factors, but also other nature factors such as elevation and soil properties, however, elevation and soil properties are hardly changed over short timescales. Moreover, human activities such as deforestation or afforestation, agricultural cultivation, and unplanned urbanization, have dramatically changed the vegetation at short time scales. Thus, at 3- and 6-year timescales, vegetation changes were mainly dominated by human activities. Only about 20% of changes in the low-altitude study area were mainly driven by climate changes. So, the relative roles of human activities and climate changes were also affected by elevation. Over the long-term trend, almost all changes in the study area were mainly driven by climate changes. Some key human activities such as the transformation from deforestation to grain for green, urbanization and the development of the west regions policy, as well as the improvements in fertilization, may also have impacts on long-term vegetation change. However, when taking 3- and 6-year timescales and long-term trend as whole, climate changes dominated vegetation changes in most areas where human activities dominated at 3- and 6-year timescales. Thus, it is possible because climate changes dominated the long-term trend of vegetation change, which changed its dominance as a whole.

In the Qinghai–Tibet Plateau, which includes the Qinghai province,

Table 4
Percentage of total area for different relationships between growing-season NDVI and climate changes (temperature and precipitation) at different time scales (3- and 6-year timescales and long-term trend).

	IMF1 (3-year)		IMF2 (6-year)		Residue (long-term trend)	
	Temperature	Precipitation	Temperature	Precipitation	Temperature	Precipitation
$R < 0, p < 0.05$	5.17	6.01	8.30	7.65	32.17	37.04
$R > 0, p < 0.05$	7.99	5.96	13.77	20.84	67.55	62.72
$R < 0, p > 0.05$	41.07	44.77	36.46	31.10	0.12	0.12
$R > 0, p > 0.05$	45.77	43.26	41.47	40.41	0.16	0.12

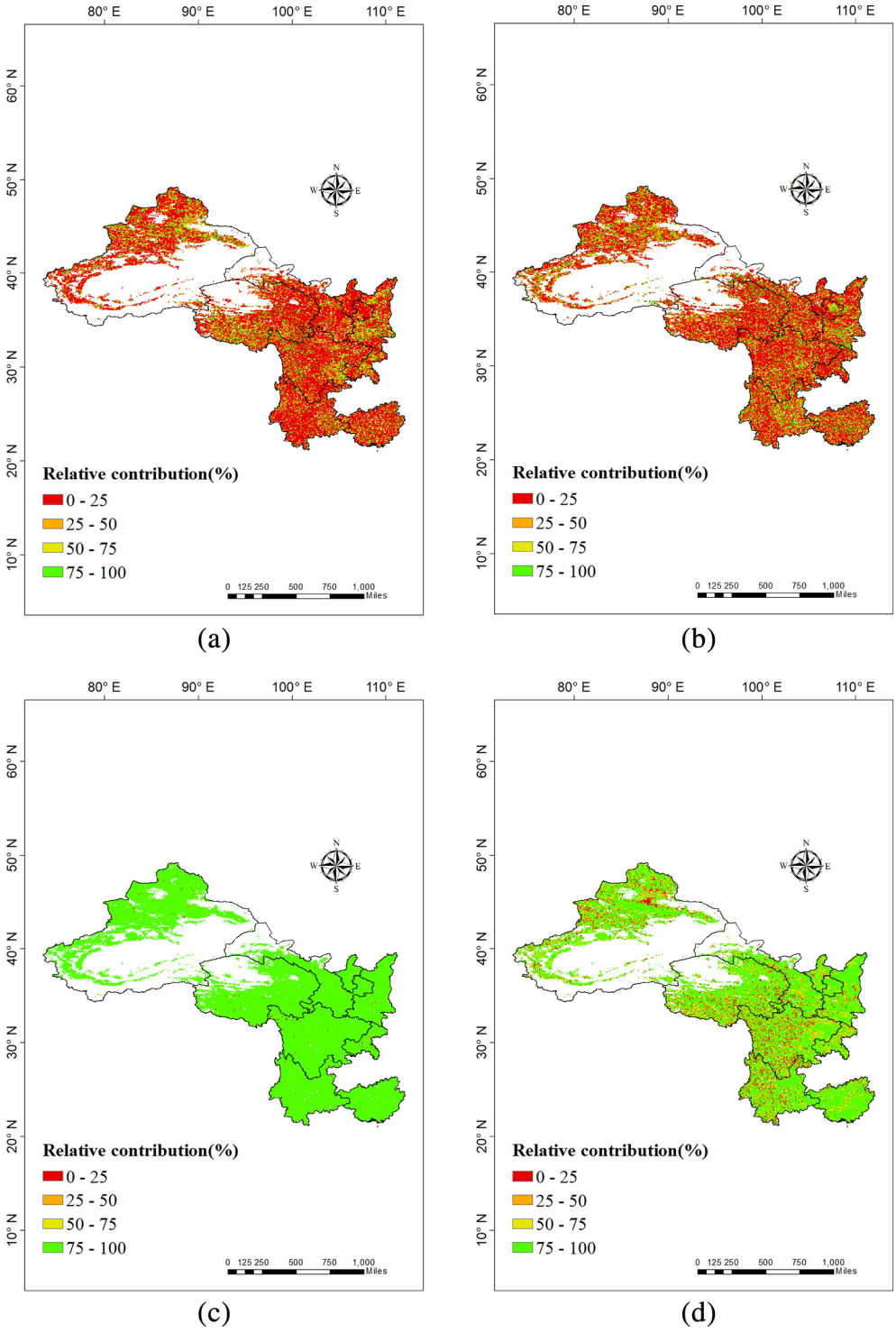


Fig. 7. Relative contributions of climate changes to vegetation dynamics at the 3-year timescale (a), 6-year timescale (b), and long-term trend (c) and as a whole (d).

climate change was the principal cause of grassland degradation, whereas human activities were the dominant factor in grassland restoration (Wang et al., 2016). Whereas in Northwest China, grassland degradation was caused by human activities, grassland restoration was caused by climatic factors (Zhou et al., 2014). However, in our study, when considering the overall effects of the dominant timescales and the long-term trend using multiple timescale analysis, vegetation increases were mainly caused by climate changes. Climate change was the principal driving force behind vegetation decreases and insignificant vegetation changes, but human activities also played important roles. Oscillations at short timescales were mainly driven by human activities and vegetation in the area characterized by short-term oscillations should, in general, be mainly driven by human activities as a whole; however, they were mainly driven by climate changes when all timescales were considered. It is possible that vegetation changes were affected by cross-scale climate changes, that is, the vegetation changes at one timescale were affected by climate changes at another timescale. Therefore, it is necessary to comprehensively reveal the relative role of climate changes and human activities based on multiple timescale analysis under a nonlinear and nonstationary assumption.

Table 5
Percentage of human-dominated and climate-dominated vegetation changes over different timescales (3- and 6-year timescales and long-term trend) and for overall changes. Relative contributions of climate changes greater than or less than 50% are thought to be climate-dominated or human-dominated.

		Significant increase	Insignificant increase	Increase	Significant decrease	Insignificant decrease	Decrease
IMF1 (3-year)	Climate-dominated	8.86	5.17	14.03	1.01	3.08	4.09
	Human-dominated	43.53	21.73	65.26	3.59	13.03	16.62
IMF2 (6-year)	Climate-dominated	11.83	6.23	18.06	1.02	3.23	4.25
	Human-dominated	41.25	20.76	62.01	3.66	12.02	15.68
Residue (trend)	Climate-dominated	55.49	25.65	81.14	5.03	13.63	18.69
	Human-dominated	0.04	0.09	0.13	0.01	0.06	0.07
Overall changes	Climate-dominated	50.02	19.12	69.14	4.41	10.43	14.83
	Human-dominated	2.21	7.55	9.76	1.55	4.71	6.26

Vegetation changes are mainly driven by human activities over interannual timescales. Economic development and population increase as a result of the One Belt and One Road Initiative will thus pose great threats to vegetation over short timescales. Especially, in semi-arid and arid areas, increasing temperature will prevent vegetation growth at short timescales, which will exacerbate vegetation deterioration from human activities at short timescales. Although climate changes can favor vegetation growth over the long term and mitigate human effects on vegetation, there is no significant increase in precipitation, which will weaken the positive impacts of climate changes. Therefore, to ensure sustainable socioeconomic development in the Silk Road Economic Belt, and particularly in arid and semi-arid regions, vegetation should be protected from human activities to prevent ecosystem loss from extending from the short term to the long term.

5. Conclusion

Using the EEMD method, the growing-season NDVI of the China's Silk Road economic belt can be divided into 3-, 6-, 15- and 32-year timescales and a long-term trend over the past 34 years. Vegetation changes were dominated by 3-year timescale and long-term trend with obvious spatial heterogeneity. Needleleaf forest, shrubland and high-altitude areas dominated by grassland were characterized by 3-year vegetation oscillations and low-altitude areas dominated by cropland were characterized by a long-term trend.

The relationships between vegetation and climate change varied over different timescales due to different driving forces. Climate types affected the relationship at short timescales, while vegetation types, elevation and landform affected it over long-term trend. Temperature had a negative relationship with vegetation changes in semi-arid and arid regions over short timescales but a positive relationship with vegetation changes in semi-humid and humid regions. However, as the timescale widened, temperature had a positive relationship with vegetation changes in all areas except needleleaf forests. Precipitation had a positive relationship with vegetation changes in semi-arid and arid regions but a negative relationship in semi-humid and humid regions over the 3-year timescale. However, precipitation had a positive relationship with vegetation changes as timescale widened, with the exception of karst areas and high-altitude alpine meadows, which had a negative relationship with vegetation change. The correlation between vegetation and climate change became increasingly significant as the timescale widened.

Over short timescales such as 3- and 6-year, vegetation changes were mainly driven by human activities, especially in high-altitude areas. Over the long-term trend, vegetation changes were mainly driven by climate changes. For overall changes of vegetation, climate changes were the dominant driving forces in most areas, while human activities played important roles in the areas with insignificant changes or significant decrease in vegetation.

Using multiple timescale analysis with the EEMD method, vegetation changes over different timescales were explored and showed obvious spatial heterogeneity. Thus, vegetation changes should be monitored both as a whole and at different timescales. The relationships between vegetation and climate change, and the relative importance of climate changes and human activities are dependent on timescales. The nonlinearity and nonstationarity in vegetation changes means that studies based on a linear and stationary assumption are inadequate. Therefore, multiple time analysis is necessary to assess the role of different influencing factors of vegetation changes. Although RESTREND method can reveal the relative importance of climate changes and human activities, it has not considered the nonlinear effects of different influencing factors. Moreover, it cannot reveal what kinds of human activities are the main driving. Thus, further work is needed to collect long-term data of human activities for multiple time scale analysis to determine what kind of human activities are the main driving.

Acknowledgements

This research has been supported by National Natural Science Foundation of China (No. 31470519), and funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions (164320H116). The authors thank the anonymous reviewers for their helpful suggestions.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version, at https://doi.org/10.1016/j.catena.2019.04.027. These data include the Google map of the most important areas described in this article.

References

Bai, Y., Han, X., Wu, J., Chen, Z., Li, L., 2004. Ecosystem stability and compensatory effects in the Inner Mongolia grassland. Nature 431, 181–184.
Cai, H.Y., Yang, X.H., Xu, X.L., 2015. Human-induced grassland degradation/restoration in the central Tibetan Plateau: the effects of ecological protection and restoration projects. Ecol. Eng. 83, 112–119.
Du, J.Q., Shu, J.M., Yin, J.Q., Yuan, X.J., Jiaerheng, A., Xiong, S.S., He, P., Liu, W.L., 2015. Analysis on spatio-temporal trends and drivers in vegetation growth during recent decades in Xinjiang, China. Int. J. Appl. Earth Obs. Geoinf. 38, 216–228.
Duan, F., Ji, Q., Liu, B., Fan, Y., 2018. Energy investment risk assessment for nations along China's Belt &Road Initiative. J. Clean. Prod. 170, 535–547.
Evans, J., Geerken, R., 2004. Discrimination between climate and human-induced dryland degradation. J. Arid Environ. 57, 535–554.
Guo, Q., Fu, B., Shi, P., Cudahy, T., Zhang, J., Xu, H., 2017. Satellite monitoring the spatial-temporal dynamics of desertification in response to climate change and human activities across the Ordos Plateau, China. Remote Sens. 9, 525.
Hawinkel, P., Swinnen, E., Lhermitte, S., Verbist, B., Orshoven, J.V., Muys, B., 2015. A time series-processing tool to extract climate-driven interannual vegetation dynamics using Ensemble Empirical Mode Decomposition (EEMD). Remote Sens. Environ. 169, 375–389.
Holben, B.N., 1986. Characteristics of maximum-value composite images from temporal AVHRR data. Int. J. Remote Sens. 7, 1417–1434.
Hou, W., Gao, J., Wu, S., Dai, E., 2015. Interannual variations in growing-season NDVI and its correlation with climate variables in the southwestern karst region of China. Remote Sens. 7, 11105–11124.
Hua, W.J., Chen, H.S., Zhou, L.M., Xie, Z.J., Qin, M.H., Li, X., Ma, H.D., Huang, Q.G., Sun, S.L., 2017. Observational quantification of climatic and human influences on vegetation greening in China. Remote Sens. 9, 425.
Huang, S.W., Kong, J.M., 2016. Assessing land degradation dynamics and distinguishing

human-induced changes from climate factors in the three-north shelter forest region of China. ISPRS Int. J. Geo-Inf. 5, 158.
Huang, N.E., Shen, Z., Long, S.R., 1998. The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis. Proc. R. Soc. London A 454, 899–955.
Huang, K., Zhang, Y.J., Zhu, J.T., Liu, Y.J., Zu, J.X., Zhang, J., 2016. The influences of climate change and human activities on vegetation dynamics in the Qinghai-Tibet Plateau. Remote Sens. 8, 876.
Hutchinson, M.F., Xu., T., 2013. ANUSPLIN Version 4.4 User Guide. The Australian Nat. Univ., Canberra, Australia.
Jamali, S., Seaquist, J., Eklundh, L., Ardö, J., 2014. Automated mapping of vegetation trends with polynomials using NDVI imagery over the Sahel. Remote Sens. Environ. 141, 79–89.
Jiang, Z., Lian, Y., Qin, X., 2014. Rocky desertification in Southwest China: impacts, causes, and restoration. Earth Sci. Rev. 132, 1–12.
Jiang, W., Yuan, L., Wang, W., Cao, R., Zhang, Y., Shen, W., 2015. Spatio-temporal analysis of vegetation variation in the Yellow River Basin. Ecol. Indic. 51, 117–126.
Jiang, L., Jiapaer, G., Bao, A., Guo, H., Ndayisaba, F., 2017. Vegetation dynamics and responses to climate change and human activities in Central Asia. Sci. Total Environ. 599–600, 967–980.
Jiapaer, G., Liang, S.L., Yi, Q.X., Liu, J.P., 2015. Vegetation dynamics and responses to recent climate change in Xinjiang using leaf area index as an indicator. Ecol. Indic. 58, 64–76.
Kendall, M., 1975. Rank Correlation Methods. Griffin, London.
Kong, D., Zhang, Q., Singh, V.P., Shi, P., 2017. Seasonal vegetation response to climate change in the Northern Hemisphere (1982–2013). Glob. Planet. Chang. 148, 1–8.
Li, P., Qian, H., Howard, K.W.F., Wu, J., 2015. Building a new and sustainable “silk road economic belt”. Environ. Earth Sci. 74, 7267–7270.
Li, Q., Zhang, C.L., Shen, Y.P., Jia, W.R., Li, J., 2016. Quantitative assessment of the relative roles of climate change and human activities in desertification processes on the Qinghai-Tibet Plateau based on net primary productivity. Catena 147, 789–796.
Liu, Z., Menzel, L., 2016. Identifying long-term variations in vegetation and climatic variables and their scale-dependent relationships, a case study in Southwest Germany. Glob. Planet. Chang. 147, 54–66.
Liu, H., Zhang, M., Lin, Z., 2017. Relative importance of climate changes at different time scales on net primary productivity—a case study of the karst area of northwest Guangxi, China. Environ. Monit. Assess. 189, 539.
Liu, H., Zhang, M., Lin, Z., Xu, X., 2018. Spatial heterogeneity of the relationship between vegetation dynamics and climate change and their driving forces at multiple time scales in Southwest China. Agric. For. Meteorol. 256–257, 10–21.
Ma, W.Y., Wang, X.M., Zhou, N., Jiao, L.L., 2017. Relative importance of climate factors and human activities in impacting vegetation dynamics during 2000–2015 in the Otindag Sandy Land, northern China. J. Arid Land (4), 558–567.
Mann, H.B., 1945. Nonparametric tests against trend. Econometrica 13, 245–259.
Molnar, P., Boos, W.R., Battisti, D.S., 2010. Orographic controls on climate and paleo-climate of Asia: thermal and mechanical roles for the Tibetan Plateau. Annu. Rev. Earth Planet. Sci. 38, 77–102.
Pang, G.J., Wang, X.G., Yang, M.X., 2017. Using the NDVI to identify variations and responses of vegetation to climate change on the Tibetan Plateau from 1982 to 2012. Quatern. Int. 444, 87–96.
Paruelo, J.M., Epstein, H.E., Lauenroth, W.K., Burke, I.C., 1997. ANPP estimates from NDVI for the Central Grassland Region of the United States. Ecology 78, 953–958.
Piao, S.L., Wang, X., Cias, P., Zhu, B., Wang, T., Liu, J., 2011. Changes in satellite-derived vegetation growth trend in temperate and boreal Eurasia from 1982 to 2006. Glob. Change Biol. 17, 3228–3239.
Pinzon, J.E., Tucker, C.J., 2014. A non-stationary 1981–2012 AVHRR NDVI3g time series. Remote Sens. 6, 6929–6960.
Ran, Y.H., Li, X., Lu, L., 2009. China land cover classification at 1 km spatial resolution based on a multi-source data fusion approach. Adv. Int. Earth Sci. 2, 192–203.
Rishmawi, K., Prince, S.D., Xue, Y., 2016. Vegetation responses to climate variability in the northern arid to sub-humid zones of Sub-Saharan Africa. Remote Sens. 8, 910.
Sen, K., 1968. Estimates of the regression coefficient based on Kendall'stau. J. Am. Stat. Assn. 63, 1379–1389.
Sun, Y., Yang, Y., Zhang, L., Wang, Z., 2015a. The relative roles of climate variations and human activities in vegetation change in North China. Phys. Chem. Earth 87–88, 67–78.
Sun, Y., Yang, Y., Zhang, Y., Wang, Z., 2015b. Assessing vegetation dynamics and their relationships with climatic variability in northern China. Phys. Chem. Earth 87–88, 79–86.
Tong, X.W., Wang, K.L., Yue, Y.M., Brandtd, M., Liu, B., Zhang, C.H., Liao, C.J., Fensholt, S., 2017. Quantifying the effectiveness of ecological restoration projects on long-term vegetation dynamics in the karst regions of Southwest China. Int. J. Appl. Earth Obs. Geoinf. 54, 105–113.
Wang, J., Meng, J.J., Cai, Y.L., 2008. Assessing vegetation dynamics impacted by climate change in the southwestern karst region of China with AVHRR NDVI and AVHRR NPP time-series. Environ. Geol. 54, 1185–1195.
Wang, Z.Q., Zhang, Y.Z., Yang, Y., Zhou, W., Gang, C.C., Zhang, Y., Li, J.L., An, R., Wang, K., Odeh, I., Qi, J.G., 2016. Quantitative assess the driving forces on the grassland degradation in the Qinghai–Tibet Plateau, in China. Ecol. Inform. 33, 32–44.
Wen, Z.F., Wu, S.J., Chen, J.L., Lü, M.Q., 2017. NDVI indicated long-term interannual changes in vegetation activities and their responses to climatic and anthropogenic factors in the Three Gorges Reservoir Region, China. Sci. Total Environ. 574, 947–959.
Wu, Z.H., Huang, N.E., 2005. Statistical significance test of intrinsic mode functions. In: Huang, N.E., Shen, S.P. (Eds.), Hilbert-Huang Transform and Its Applications. World Sci, Hackensack, N. J, pp. 125–148.
Wu, Z.H., Huang, N.E., 2009. Ensemble empirical mode decomposition: a noise-assisted data analysis method. Adv. Adapt. Data. Anal. 1 (1), 1–41.
Xie, B.N., Jia, X.X., Qin, Z.F., Shen, J., Chang, Q.R., 2016. Vegetation dynamics and climate change on the Loess Plateau, China, 1982–2011. Reg. Environ. Chang. 16, 1583–1594.
Xu, W.X., Gu, S., Zhao, X.Q., Xiao, J.S., Tang, Y.H., Fang, J.Y., Zhang, J., Jiang, S., 2011. High positive correlation between soil temperature and NDVI from 1982 to 2006 in alpine meadow of the Three-River Source Region on the Qinghai–Tibetan Plateau. Int. J. Appl. Earth Obs. Geoinf. 13, 528–535.
Xu, Y.F., Yang, J., Chen, Y.N., 2016. NDVI-based vegetation responses to climate change in an arid area of China. Theor. Appl. Climatol. 126, 213–222.
Yin, Y., Ma, D., Wu, S., Dai, E., Zhu, Z., Myneni, R.B., 2016. Nonlinear variations of forest leaf area index over China during 1982–2010 based on EEMD method. Int. J. Biometeorol. 10, 1–12.
Zhang, Y., Zhang, J.B., Wang, Z.Q., Chen, Y.Z., Gang, C.C., An, A., Li, J.L., 2016a. Vegetation dynamics and its driving forces from climate change and human activities in the Three-River Source Region, China from 1982 to 2012. Sci. Total Environ. 563–564, 210–220.
Zhang, R., Tao, Z., yang, O., Xie, X., Guo, H.Q., Tan, D.Y., Xiao, X.M., Qi, J.Q., Zhao, B., 2016b. Impact of climate change on vegetation growth in arid northwest of China from 1982 to 2011. Remote Sens. 8, 364.
Zhou, W., Gang, C.C., Zhou, L., Chen, Y.Z., Li, J.L., Ju, W.M., Odeh, I., 2014. Dynamic of grassland vegetation degradation and its quantitative assessment in the northwest China. Acta Oecol. 55, 86–96.